Remarks

Objection to the Specification

The specification is objected to as adding new matter, specifically, the "newly inserted text corresponding to the listed references in the specification". Although the listed references were included in the originally filed International Application and so are not believed to be new matter, the specification has been amended herein to remove the references and the references to the references. Withdrawal of the objection to the specification is respectfully requested.

Rejections of Claims 18-22, 28-32, and 39-40 under 35 USC 101

Claims 18-22, 28-32, and 39-40 are rejected as being drawn to non-statutory subject matter on the basis of two grounds: being drawn to an abstract idea, and because the specification refers to "signals transmitted in the network". Each ground will be discussed separately below.

Abstract Idea. The examiner states "[t]he Courts have found that subject matter that is not a practical application or use of an idea, a law of nature, or a natural phenomenon is not patentable...the claims are directed merely to an abstract idea that is not tied to a technologic art, environment, or machine that would conclude with a tangible result [emphasis in original] to [be statutory subject matter]. The claimed methods appear to be no more than manipulation of mathematical equations and data manipulation without any application or tangible output [emphasis in original]...".

As an initial matter, the "application and tangible output" test referred to by the examiner was replaced in In re Bilski (citation omitted) with the machine or transformation test. See, for example, Ex parte Borenstein, Application 10/785,839 (Bd. Pat. App. & Interf. March 30, 2009) where the Board stated on page 9 "...regarding the non-statutory test, the useful, concrete, and tangible result requirement was replaced in In Re Bilski with the machine-or-transform test."

Claim 18 has been amended herein to recite a system comprising a computer processor and a memory and is therefore not a method claim that must be analyzed under Bilski.

Claim 28 has been amended herein to recite a system comprising a computer and a memory and is therefore not a method claim that must be analyzed under Bilski.

And even if the steps recited in claims 18 and 28 are analyzed under the Bilski machine-or-transform test, the claims would satisfy such a test for patentable subject matter. In both claims the steps are tied to a particular machine, and involve the transformation of data (which is the entire purpose of an artificial neural network).

Signal. The examiner observed that paragraph 27 of the specification "states 'signals transmitted in a network'. Signals are non-statutory and therefore the Examiner requests clarification as to how the method claims do not encompass the recited signals" [emphasis in the original].

Although the examiner has not cited the basis for his assertion that signals are non-statutory, applicant believes the examiner is referring to In re Nuijten, 500 F.3d 1346 (Fed. Cir. 2007) in which the independent claim at issue read:

> A signal with embedded supplemental data, the signal being encoded in accordance with a given encoding process and selected samples of the signal representing the supplemental data, and at least one of the samples preceding the selected samples is different from the sample corresponding to the given encoding process.

The court held that a claim to a signal was not drawn to statutory subject matter because the signal is not an article of manufacture.

None of the pending claims in the instant application are drawn to a signal.

It must be emphasized that Nuijten does not hold for the proposition that claims that "encompass" signals or are otherwise related to signals are automatically non-statutory. The claims allowed in the Nuijten application include a method for embedding supplemental data in a signal, an arrangement for embedding supplemental data in a signal, and a storage medium having stored thereon a signal with embedded supplemental data.

Based on the foregoing, reconsideration and withdrawal of the Section 101 rejections of claims 18-22, 28-32, and 39-40 are respectfully requested.

Examiner's Response to Previous Prior Art Arguments

In the examiner's response to arguments, the examiner notes "that the claim recites an 'or' clause and as such the Examiner

has cited a reference which reads [on one branch of the 'or' clause]."

Claims 18 and 28 has been rewritten herein to remove the "or" clause, rendering a response by the applicant to the examiner's cited reference.

The examiner also states the "reference [Tsuruta et al. 2000] recites on page 50 left column, a solution in which the original images were not used as input data but rather a Euclidean and mahalanobis distance between the input and eigenfaces therefore not entirely input dependent."

The examiner is apparently referring to the Sung and Poggio reference ("Sung"). Sung discloses a method of detecting human faces in photographs. As understood, 19 x 19 pixel images of canonical faces are generated. Edge portions of the images are masked, apparently resulting in each canonical face image having 283 pixels of information. The distribution of the canonical face images in the 283-dimension vector space is divided into "k" clusters ("k" is arbitrarily chosen to be 6) using the well-known k-means clustering algorithm.

The six cluster centroids or codebooks are initially calculated using the Euclidean distance measure. The six codebook locations are then recalculated using the Mahalanobis distance measure, which better fits elliptically shaped cluster sets (Sung believes the cluster distributions are more locally elongated along certain vector space directions than others). The six cluster centroids and the cluster covariance matrices

represent the "positive" distribution of face images in the 283-dimension vector space.

Sung also processes the cluster distribution of "non-face" 19 x 19 images in the 283-dimension vector space. These "negative" clusters help model concavities within the "positive" clusters of face images in the vector space.

The resulting 12 centroids and associated cluster covariance data is used as data in training a multi-layer perceptron to distinguish faces from non-faces within a 19 x 19 matrix of pixels taken from an image. A multi-layer perceptron does not involve topology-preserving mapping nor codebooks as is recited in claims 18 and 28. Thus the input data referred to by the examiner with respect to the multi-layer perceptron does not teach, suggest, or make obvious or suggest or make obvious the limitations recited in claims 18 and 28 that include topology-preserving mapping and codebooks.

A copy of Sung and Poggio, Example-based Learning for View-based Human Face Detection, Massachusetts Institute of Technology Artificial Intelligence Library, December, 1994, is included with the Information Disclosure Statement filed herewith.

Rejection of Claims 18-22, 28-32, and 39-40 under USC 102(b)

Claims 18-22, 28-32, and 39-40 are rejected under 35 USC 102(b) as being anticipated by Tsuruta et al. "Hypercolumn Model: A Combination Model of Hierarchical Self-Organizing Maps and Neocognitron for Image Recognition" (hereinafter "Tsuruta").

Independent claims 18 and 28 are amended herein, rendering the rejections moot. Amended claims 18 and 28 are patentable over the prior art of record.

Amended claim 18 is drawn to a system for generating codebook objects for an artificial neural network from input data that includes a processor, a memory coupled to the processor, and computer code loaded into the memory for executing on the processor, for implementing the following functionality:

(a) providing data objects to be processed as input data and providing data objects of exploration space;

(b) generating a topology-preserving mapping, by:

(i) ordering neurons in ordering space, according to a given pattern;

(ii) assigning codebook objects in outcome space to the neurons;

(iii) processing codebook objects according to the calculation rule of a topology-preserving mapping, by use of data objects of the exploration space; and

(iv) outputting the processed codebook objects as output data;

(c) determining the initial order of neurons in the ordering space by using at least a part of the provided data objects, and

(d) providing data objects of the exploration space which are independent of the input data.

Amended claim 28 is drawn to a computer implemented system for determining the cluster validity of an artificial neural network that includes a computer processor coupled to a memory, the memory containing computer code for performing the following steps:

(a) storing data objects as input data;

(b) storing distance objects between these data objects;

(c) assigning the data objects to be processed to groups by:

(i) processing the data objects by using a topology-preserving mapping, by:

(1) ordering neurons in ordering space, according to a given pattern;

(2) assigning codebook objects in outcome space to the neurons;

(3) processing codebook objects according to the calculation rule of a topology-preserving mapping, by use of data objects of the exploration;

(4) outputting the processed codebook objects as output data;

(ii) both of the following substeps (1) and (2):

(1) determining the initial order of neurons in the ordering space by using at least a part of the provided data objects;

(2) providing said data objects that are independent of the input data to be processed and which are used as data objects of the exploration space;

(d) outputting a measure of the quality of this assignment as output data; and

(e) calculating the measure of the quality of the assignment by employing at least a part of the provided distance objects.

The amended claims do not include new matter; the basis for the amendments are found in paragraphs 0027-0030 of the application as filed, which includes reference to a computer, processing system, and memory.

As to claims 18 and 28, the examiner asserts that Tsurutu discloses:

* determining the order of neurons in the ordering space by using at least a part of the provided data objects, citing page 55, top right, and

* providing data objects of the exploration space which are independent of the input data, citing section 2.1, "a characteristic of the SOM is that the distance between neurons and the neighborhood of each neuron are defined independently of the data space."

Tsurutu discloses the Hypercolumn Model ("HCM") is a neural network formed as a combination of two different neural networks: the Hierarchical Self-Organizing Map ("HSOM") and the NeoCognitron ("NC").

The HSOM is a multilayer self-organizing map. See Lampinen et al., "Clustering Properties of Hierarchical Self-Organizing Maps", Journal of Mathematical Imaging and Vision 2, pp. 261-272 (1992) previously provided.

An HSOM consists of a first self-organizing map (the first layer) and a second self-organizing map (the second layer), each map having a predetermined number of neurons. The maps become self-organized using the Kohonon algorithm (described in the "Background of the Invention" section of the specification under the heading "Self-Organizing Maps" [which includes paragraphs [012]-[020] of the published patent application]).

For each input vector, the best matching neuron is chosen from the first layer and its index *b* is input to the second layer. The best matching unit for *b* is chosen from the second layer map and its index is the output of the network.

A Neocognitron is a self-organizing neural network used for classifying 2-dimensional visual patterns. See Fukishima, "Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by a Shift in Position," Biol. Cybernetics 36, 193-202 (1980), previously provided.

The NeoCognitron ("NC") has a 2-dimensional input layer that represents the retina and a number of modular stages or structures that extend "downstream" from the input layer. Each stage extracts appropriate features from the output of the preceding stage and then forms a compressed representation of

those extracted features. Classification is achieved by repeatedly extracting and compressing representations until the input is reduced to a representation the NC has been trained to identify.

Each modular stage is composed of two layers, the S-layer and the C-layer, connected in a cascade. The S-layer extract local features and the C-layer integrate shifted features. Each S-Layer and C-Layer is made up of a predefined number of cells or neurons. Using this structure, the NC reduces dimensionality gradually and can recognize shifted and scaled patterns.

Tsuruta points out that the NC has disadvantages with complex images due to the low reduction rate of the coding scheme and an initial state dependency of competitive learning. The competitive learning used in the NC is not powerful and so for each layer suitable learning data must be generated by hand.

The HCM is constructed by replacing the modular stages of the NC and "pyramidally piling up Lampinen's HSOM similarly to the NC", Tsuruta Section 3.1, page 53. The HSOM layers enable self-organization using Kohonen's SOM algorithm to generate feature maps that preserve the topographic order of the sample data, and to increase the reduction rate of the dimensionality of the feature maps.

The HCM combines a bottom-up feature extraction mechanism provided by training of HSOMs and a top-down recognition process that uses the results obtained by the HSOMs. The top-down recognition process is based on a method described in detail in

Tsuruta et al. 1999, Section 3.3. From this description, it is clear that the feature extraction mechanism in the HSOM is not influenced by the top-down recognition process in the HCM. Specifically, the top-down recognition process does not influence the training procedure of the HSOM, <u>nor does it introduce a topology-preserving mapping</u> that is not related to the HSOM. Thus, the only learning procedure in the HCM model that involves topology-preserving mappings is the learning procedure of the HSOM itself, and so it is only the HSOM portion of the HCM that includes topology-preserving mapping and is relevant to the claims.

Tsuruta 1999 Section 3.3 contains pseudocode describing the training process for a feature map in each HSOM layer. The training of the topology-preserving mapping in the HCM is essentially identical to the topology-preserving mapping in the HSOM according to Lampinen et al., that is, both HCM and HSOM use Kohonen's algorithm for self-organization of the neurons.

A brief description of the Kohonen SOM algorithm is given below. The Kohonen SOM is a topology-preserving mapping that exhibits self-organizing effects by its learning scheme, enabling topographical mapping of data in a higher dimensional vector space to a lower dimension vector space.

In the Kohonen SOM algorithm, the data objects of the ordering space (also known as ordering objects or neurons) are determined by a structural hypothesis. "The neurons are arranged to a 1-, 2-, or multidimensional *lattice* such that each neuron

has a set of neighbors," Lampinen et al, page 3. In Tsurutu the structural hypothesis was to use one-dimensional maps, although the HCM could use higher-dimensional maps (that is, the HCM could use different structural hypotheses).

Each neuron j of the Kohonen SOM is associated with a weight vector or codebook vector Wj. To self-organize the SOM, all neurons are fed the same input data I. The input data I defines the exploration space of the Kohonen SOM algorithm, that is, the set of data objects with which the topology-preserving mapping is trained. The codebook vectors W define the outcome space resulting from the processing of the input data.

In the Kohonen SOM algorithm the input data I and the codebook vectors W have the same dimensionality, which is independent of the dimensionality of the structural hypothesis defining the neuron lattice. In Tsuruta the dimension of the exploration space is 2 (the HCM described in Tsuruta was trained using a number of two-dimensional images) but the nodes are arranged as a 1-dimensional lattice.

Training the Kohonen SOM to determine the outcome space consists of iterating through the members of the exploration space and presenting each member to all the neurons of the ordering space. In each iteration the best matching neuron is selected (the "winner") and the weights of the codebook vectors of the winning neuron and the neurons in the geometric neighborhood of the winning neuron are adapted. The size of the neighborhood decreases with each iteration, and typically the

learning rate decreases as well. Techniques for selecting the winning neuron, defining the neighborhood around the winning neuron, and adaption of the codebook vectors are described in greater detail in the application for the Kohonen SOM algorithm and so will not be repeated here.

The only difference in the Kohonen SOM algorithm used in Lampinen et al. and the Kohonen SOM algorithm used in Tsurutu is that Tsurutu et al. eliminates those neurons that were not selected as a winner in the previous training iteration. As this elimination occurs after the last iteration of the training procedure, i.e. after the training of the HSOM is completed, it is obvious this elimination step is not related to the learning of the HSOM's topology-preserving mapping. It is merely simple "pruning" of non-used neurons after the Kohonen SOM algorithm has been completed.

The examiner asserts Tsuruta discloses determining the order of neurons in the ordering space by using at least a part of the provided data objects, citing page 55, top right. This portion of Tsuruta describes the specification of the HCM, that is, the number of neurons, the dimensionalities of the maps, the feature integration rates, and the interest operator.

Tsuruta discusses the number of neurons used for the layers of the HCM (each layer being a SOM) but <u>does not</u> discuss the order of the neurons in the ordering space. Tsuruta does not determine the initial order of the neurons in the ordering space

by using at least a part of the provided data objects as recited in claims 18 and 28.

The examiner also asserts Tsuruta discloses providing data objects of the exploration space which are independent of the input data, citing section 2.1, "a characteristic of the SOM is that the distance between neurons and the neighborhood of each neuron are defined independently of the data space."

Two important features of the Kohonen SOM algorithm are first, that the structural hypothesis is independent of the exploration space, and secondly, that the input data defines the exploration space.

In the conventional SOM algorithm (such as the Kohonen SOM algorith) the structural hypothesis is independent of exploration space (the set of data being used to train the neurons). Tsururata's statement that a characteristic of the SOM is that the distance between neurons and the neighborhood for each neuron are defined independently of the data space merely reiterates the first characteristic of the Kohonen SOM algorithm referred to above, that the structure hypothesis is independent of the exploration space. Such a statement does not encompass, teach, or suggest providing <u>data objects</u> that are independent of the input data to be processed and which are used as data objects of the exploration space as recited in claims 18 and 28.

In the following, the fundamental differences between the HCM learning procedure described in detail in Tsuruta et al. 2000 and the present invention is described. The pseudocode

statements used by Tsuruta et al. 2000, Section 3.3 in order to provide a detailed description of the learning of the topology-preserving mapping in the HCM refer to equations (1) and (2) of section 2.1 of the Tsuruta et al. 1999 paper. Equation (3) defines the cooperativity function h_{cu} in equation (2). According to the terminology used in the present patent application description, the following correspondences to Tsuruta et al. 2000 apply - terms used in the present patent application description are printed in ***bold italic:***

The symbols r_c and r_u in equation (3) of Tsuruta et al. 2000 correspond to the positions of the neurons in the ***ordering space*** of the topology-preserving mapping. These positions are <u>not</u> influenced by the ***input data*** *I,* i.e. they clearly represent a ***structure hypothesis*** (note that Tsuruta et al. 2000, section 2.1 clearly identifies the patterns *I* as "input data"), only the weight vector W_u that is associated with each neuron *u* is updated according to the iterative learning rule in equation (2). According to equation (2), the input data patterns *I* are presented in the ***exploration space*** of the topology-preserving mapping, whereas the weight vectors W_u belong to the ***output space*** of the topology-preserving mapping, which in the case of the HCM, has the "same dimensionality as [the input data] *I*" (Tsuruta et al. 2000, Section 2.1).

With these correspondences, it is clear that in the HCM, as described in Tsuruta et al. 2000, the ***input data*** is presented in the ***exploration space*** of the topology-preserving mapping, and the

ordering of the neurons in the ***ordering space*** represents a ***structure hypothesis.*** Thus, the training of the topology-preserving map in the HCM exactly corresponds to the training of topology-preserving mappings according to the prior art, i.e. "the exploration space is thus assigned to the input data and the ordering space is assigned to the structure hypotheses" as stated in this patent application describing the prior art..

Specifically, the learning procedure in HCM (as well as in HSOM), is <u>not</u> *"determining the order of neurons in the ordering space by using at least a part of the provided [input] data objects"* as recited in claims 18 and 28, i.e., the positions r_u of the neurons u in the ordering space are <u>not</u> determined by the input data I. Only the weight vector W_u belonging to each neuron u is computed based on the input data I according to equations (1)-(3) in Tsuruta et al. 2000; the neuron positions r_u in the ordering space, however, are **not** influenced by the input data I, as can clearly be seen from equations (1)-(3) in Tsuruta et al. 2000. This fact is even explicitly stated by the sentence quoted by the examiner: "A characteristic of the SOM is that the distance between neurons and the neighborhood for each neuron <u>are defined independently of the data space</u>," Tsuruta et al. 2000, Section 2.1 - that is, the order of the neurons in the ordering space is <u>not</u> influenced by the provided input data objects.

Moreover, the learning procedure in HCM (as well as in HSOM), is <u>not</u> providing data objects which are independent of the input data to be processed" <u>and</u> which are used as data objects of

the exploration space as recited in claims 18 and 28, as can be seen from equations (1)-(3) in Tsuruta et al. 2000 as well. Equations (1)-(3) show that, besides the input data *I*, there are no additional data objects of the exploration space other than *I*, i.e. there are no training patterns not related to *I* which could be used for training of the topology-preserving mapping.

For the reasons stated above, Applicant believes that Tsuruta does not include either the steps of:

- determining the initial order of neurons in the ordering space by using at least a part of the provided data objects, and
- providing data objects of the exploration space which are independent of the input data

as recited in claims 18 and 28, and certainly does not include both steps as recited in claims 18 and 28.

Based on the foregoing, reconsideration and withdrawal of the rejections against amended claims 18 and 28 are respectfully requested. As the remaining claims depend from allowable claims, reconsideration and withdrawal of the rejections of the remaining pending claims are also respectfully requested.

Conclusion.

This amendment places the application in condition for allowance. If issues remain, the examiner is invited to telephone the undersigned to discuss resolution of same.

Respectfully submitted,

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